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Deep Learning in Agritech: Exploring Techniques and Architectures for Plant Disease Detection

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Abstract: - Disease detection in agriculture is crucial for maintaining crop health and productivity. Traditional methods of detection rely on manual observation and expert knowledge, which can be time-consuming and subjective. In recent years, deep learning techniques have emerged as a promising approach for automated disease detection. This paper investigates the performance of three state-of-the-art deep learning models, ResNet34, MobileNetv2, And Yolov8, in detecting and categorizing leaf diseases among corns. The study revealed that MobileNet2 demonstrates computational effectiveness in classifying corn leaf diseases, with a low average loss and the ability to discriminate between specific illnesses. Yolov8 is identified as a strong candidate for real-world applications due to its consistently high precision (95.73%), recall (94.81%), accuracy (96.18%), and F1 score (95.22%) across all disease categories. It excels in distinguishing between Blight and Common Rust and accurately recognizing healthy leaves. ResNet34 and MobileNetv2 also show competitive results, but Yolov8 performs better overall, particularly in terms of precision and recall. However, the choice of the optimal model depends on the specific application's demands, computational effectiveness, and the balance between recall and precision. Further investigation and refinement endeavors are recommended to augment the potential of these models and address any remaining obstacles in disease identification.

Keywords: Disease Detection, Deep Learning in Agriculture, Artificial Intelligence in Agriculture, Machine Learning

I. INTRODUCTION

Pest and disease identification in agriculture is of utmost importance for the protection and preservation of crop yields. The control of crop pests and diseases is crucial for maintaining agricultural productivity and ensuring food security [1]. Early identification of plant diseases and pests can help prevent the spread of these issues and reduce the need for toxic chemical interventions [2]. Additionally, accurate identification of pests and diseases allows for targeted and effective treatment, minimizing the negative impact on crop yield and quality [3].

In recent years, there has been a growing interest in the application of deep learning in various domains. This successful application in other fields has attracted the attention of many researchers, leading them to explore its potential in the agricultural field. These algorithms have shown promising results in various applications, including plant disease detection, weed identification, land cover classification, fruit counting, and crop type classification [4]. The use of deep learning models in agriculture has gained attention due to their ability to handle large datasets, such as high-resolution images. Deep learning models have been found to outperform classical machine learning methods, particularly in large datasets such as high-resolution images used in agricultural research [5]. One area where deep learning techniques have shown excellent performance is in object detection and classification.

Lately, there has been a notable surge in scholarly attention toward the utilization of deep learning algorithms to identify diseases affecting crops [6] due to their ability to effectively process and analyze large amounts of data. This emerging technology offers the potential to revolutionize the way diseases are detected and managed in agriculture. With the advancements in artificial intelligence and big data technology, deep learning models have become a promising approach for real-time detection and early warning of crop diseases [7]. These models can provide accurate and timely identification of pests and diseases, allowing farmers to take appropriate measures to prevent further damage and ensure optimal crop yield and quality. Some of the different deep learning algorithms used in this field include fuzzy recognition technology, support vector machine (SVM), back propagation (BP) neural network, convolutional neural network, Model Ensemble with Inception Module and Cluster Algorithm, and Residual Neural Network (ResNet). These different deep learning algorithms offer robust and accurate

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solutions for the identification of crop diseases and pests. They leverage advanced techniques in artificial intelligence and computer vision to improve the efficiency and effectiveness of pest and disease management in agriculture [8], [9] .

Several studies using deep learning algorithms have been successfully developed to detect various crop diseases [10]. Researchers have developed real-time object detection models for identifying orchard pests [11]. Transfer learning and convolutional neural networks have been used for the recognition of crop diseases and insect pests [12]. An improved Yolov4 algorithm has been proposed for tomato pests recognition [12]. Efficient data-driven crop pest [1] identification methods based on edge distance-entropy have been developed [6]. An identification algorithm based on an improved DenseNet model has been implemented for crop pests and diseases [7]. Deep convolutional neural networks have been used for mobile capture device-based crop disease classification [13]. An improved Yolov5 network model has been proposed for agricultural pest detection [14].

Based on existing literature, deep learning algorithms such as ResNet, MobileNetv2, and Yolov8 are being used in agriculture for various purposes. ResNet is used for crop disease identification and seed classification, providing accurate results with its multi-level architecture [15]. MobileNetv2 is preferred for seed classification due to its simple architecture and memory-efficient characteristics, achieving high accuracies in different seed classes [16]. Yolov8 is used for real-time identification of plant diseases, offering efficient and accurate image assessment with its advanced object identification approach [17]. Additionally, Yolov8 has outperformed conventional object identification algorithms in terms of speed and accuracy, making it a leading solution for object detection and recognition in real-world scenarios. These deep learning models have revolutionized agriculture by overcoming the limitations of traditional machine learning approaches and providing valuable insights for crop management and yield estimation.

This research aims to provide a thorough evaluation of the effectiveness of Yolov8, MobileNetv2 and ResNet34 models, applied in the context of plant disease identification. The findings of this can inform the development of evidence-based strategies and interventions, leading to more effective and sustainable disease control measures. This highlighted the effectiveness of deep learning models in achieving high accuracy in disease detection.

II. METHOD

Within this framework, three models have been taken into account such as ResNet34, MobileNetv2, and Yolov8 - models that are considered state-of-the-art and solving image recognition tasks successfully. Using a large and comprehensive dataset from the publicly accessible PlantVillage dataset on Kaggle that has corn leaf images distributed in four different classes—Common Rust (1306 images), Gray Leaf Spot (574 images), Blight (1146 images), and Healthy (1162 images) the study investigated how well these models would detect and categorize corn leaf diseases.

Each model goes through a strict training set up containing the same method conducting 30 epochs in each cycle of its training. Being trained by such a large and varied dataset with images from all the disease classes, the models have learned to generalize even the finesse of these diseases. The depth and breadth of the dataset provided a strong footing for measuring the models' ability to generalize, not only across messages but across different settings - a requisite characteristic of such models for real-world adaptability.

III. RESULTS AND DISCUSSION

The agriculture sector plays a pivotal role in global food security, making early detection and management of crop diseases imperative for maintaining yield and quality. In recent years, deep learning algorithms have emerged as promising tools for automating disease detection processes in crops. This section presents the results of employing three state-of-the-art deep learning architectures – ResNet34, MobileNetv2, and Yolov8 – for disease detection in corn plants.

1. Corn Leaf Classification

Corn leaf data was utilized for disease detection in order to develop a model that can accurately identify and classify different types of diseases affecting corn plants. As seen in Figure 1, the data used four distinct corn leaf classifications from the Plant Village dataset, comprising one class of healthy corn leaves and three classes of corn disease leaves. This data was used to train a machine learning algorithm such as Yolov8, ResNet34 and

MobileNetv2, which learned patterns and features in the images that are indicative of different diseases. The algorithm then utilized this learned information to analyze new images of corn leaves and accurately classify whether they are healthy or affected by a specific disease.

FIGURE 1. CORN LEAF CLASSIFICATION

2. Accuracy of Models per Epoch

The evaluation accuracy of the Yolov8, ResNet34, and MobileNetv2 models in Figure 2 offers important information about how well each model performed in the task of classifying corn leaf diseases.

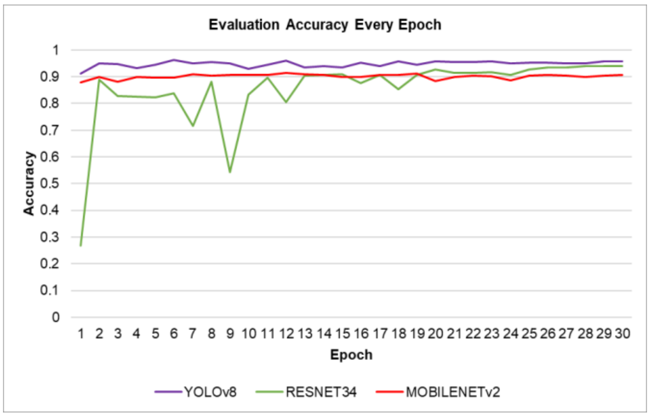

FIGURE 2. EVALUATION OF ACCURACY OF SELECTED MODELS PER EPOCH

With an average accuracy of 95.2%, Yolov8 consistently achieves high accuracy across multiple epochs. This indicates that the model has a strong track record of correctly classifying corn leaf diseases throughout the training phase. Conversely, ResNet34 shows a fluctuating accuracy trend, ranging from 54.2% to 93.6%. The observed variability encourages additional research into the variables affecting the model's performance, such as possible difficulties encountered during training or problems unique to the data. Interestingly, MobileNetv2 exhibits a 90.5% average accuracy rate, which is consistently high and shows that it is effective in producing accurate predictions while preserving computational efficiency—a critical factor for mobile and edge devices. In the context of corn leaf disease classification, this thorough examination of accuracy metrics highlights the advantages and possible drawbacks of each model, enabling possible users well-informed choices about model selection and optimization techniques.

3.Loss Data of Models per Epoch

A relevant understanding of the effectiveness of three different models—Yolov8, RESNET34, and MobileNetv2—in the context of corn leaf disease classification is provided by the evaluation loss data shown in Figure 3.

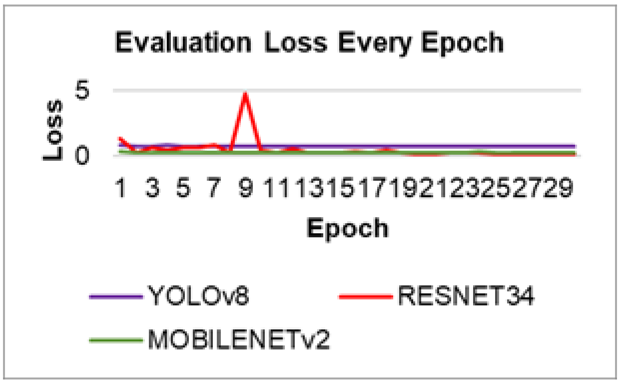

FIGURE 3. EVALUATION LOSS OF SELECTED MODELS PER EPOCH

The models were trained over several epochs, and there are clear patterns of convergence evident in the corresponding loss values.

With an average loss of 0.803, Yolov8, which is well-known for its real-time object detection abilities, exhibits steady convergence, suggesting that it is learning throughout the training phase. On the other hand, ResNet34 displays a more variable behavior, with sporadic loss spikes, which calls for additional research into possible issues encountered during training. Interestingly, MobileNetv2, intended for edge and mobile devices, sustains a comparatively low average loss of 0.303, demonstrating its computational effectiveness in addressing the task of classifying corn leaf diseases.

The results of the study corroborated with that of [18] which achieved a high level of accuracy, up to 99.93%, in detecting Robusta coffee leaf diseases using the MobileNetV2 model. Moreover, the studies of [19], [20] demonstrate the successful application MobileNetv2, in achieving accurate and reliable classification of various plant diseases.

4. Normalized Confusion Matrix of Yolov8

Figure 4 shows the normalized confusion matrix when assessing the classification of corn leaf diseases using Yolov8.

The confusion matrix offers important information about how well the model performs in various disease categories. The diagonal elements, which show the true positive rates for each class, demonstrate the high degree of accuracy displayed by the matrix. The model's remarkable accuracy in distinguishing between Blight (0.92), Common Rust (0.97), and Gray Leaf Spot (0.93) underscores its capacity to differentiate between these particular illnesses.

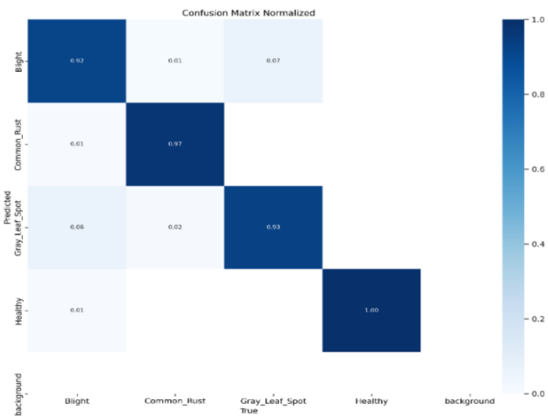

FIGURE 4. NORMALIZED CONFUSION MATRIX OF YOLOV8

Furthermore, the Healthy class's flawless precision and recall scores of 1.00 indicate the model's strong ability to correctly classify corn leaves free of disease. However, there is a small misclassification in the Blight category (false positive rate of 0.07), which indicates that there are times when the model mistakenly labels a healthy leaf as diseased

The work of Hejmanowska et al., (2021) also achieved an unexpectedly high accuracy of 79% in the classification of crops using a limited number of Sentinel-2 images.

5. Normalized Confusion Matrix of ResNet34

Figure 5 shows the normalized confusion matrix when the corn leaf disease dataset was trained using the ResNet34 model.

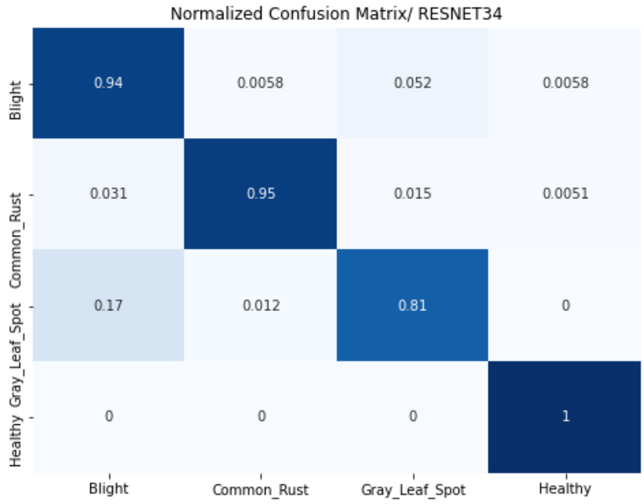

FIGURE 5. NORMALIZED CONFUSION MATRIX OF RESNET34

The model performs admirably across various disease classes, as evidenced by the confusion matrix that is provided in the ResNet34 evaluation of corn leaf disease classification. For each class, the matrix shows clear true positive rates along the diagonal elements, indicating a high degree of accuracy. In particular, ResNet34 demonstrates strong accuracy in detecting Blight (0.94), Common Rust (0.95), and Gray Leaf Spot (0.81), demonstrating its ability to discriminate between these particular illnesses. Furthermore, the model's flawless recall and precision scores for the Healthy class (1.00) highlight its capacity to recognize disease-free maize leaves with accuracy. Interestingly, there is a small misclassification in the Blight category (0.052 false positive rate), which suggests that there are times when the model mistakenly reports a healthy leaf as diseased.

6. Normalized Confusion Matrix of MobileNetv2

Using MobileNetv2 to assess corn leaf disease classification, the confusion matrix shown in figure 6 demonstrates the model's strong performance in a range of disease classes.

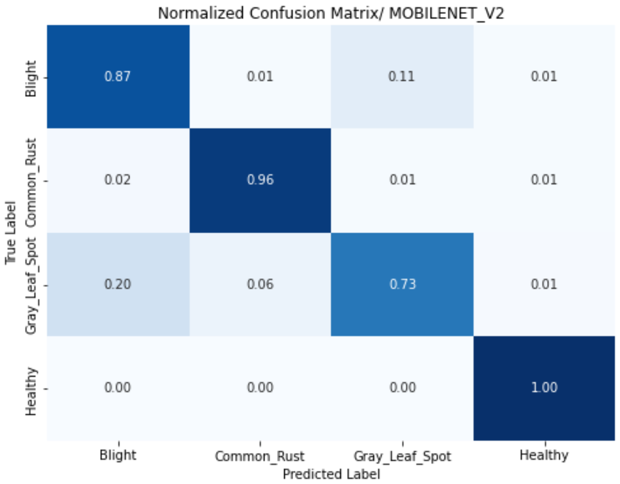

FIGURE 6. NORMALIZED CONFUSION MATRIX OF MOBILENETV2

The dominant true positive rates along the diagonal elements corresponding to each disease category show that the matrix has a high degree of accuracy. When distinguishing between Blight (0.87), Common Rust (0.96), and Gray Leaf Spot (0.73), MobileNetv2 demonstrates remarkable accuracy, demonstrating its effectiveness in differentiating between these particular illnesses. Moreover, the Healthy class's perfect precision and recall scores of 1.00 highlight the model's ability to correctly identify corn leaves free of disease. Although there is a small misclassification in the Blight category (false positive rate of 0.11), meaning that the model sometimes misclassifies a healthy leaf as diseased, overall performance is still excellent.

7. Performance Metrics per Model

The performance metrics for MobileNetv2, ResNet34, and Yolov8 as shown in Figure 7 corn leaf disease classification highlight the effectiveness of each model in the task.

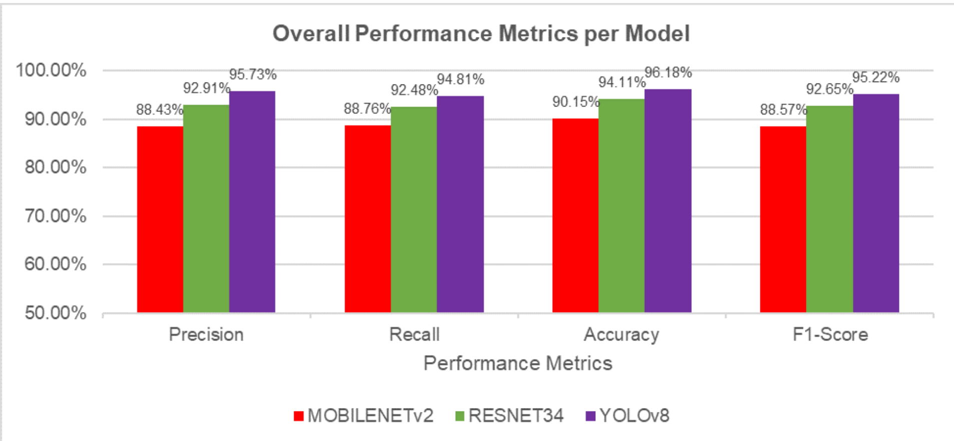

FIGURE 7. PERFORMANCE METRICS PER MODEL

With great recall (88.76%) and precision (88.43%), MobileNetv2 achieves an F1-score of 88.57% and an impressive overall accuracy of 90.15%. With greater recall (92.48%) and precision (92.91%), RESNET34 achieves an impressive accuracy of 94.11% and an F1-score of 92.65%. With the greatest recall (94.81%) and precision (95.73%), Yolov8 stands out. This translates to an excellent accuracy of 96.18% and an F1-score of 95.22%. All three models perform well overall, as shown by these metrics, with Yolov8 showing the best precision and recall. The models' high accuracy and F1-scores indicate that they are skilled at classifying corn leaf diseases. The selection of one of these models may be contingent upon particular application needs and factors, such as the importance of recall, precision, or overall accuracy in real-world deployment situations. Additional investigation and refinement endeavors may augment the potential of these models and tackle any residual obstacles in the identification of diseases.

The results corroborated with the studies of [21], [22], [23] that provide evidence of the effectiveness of YOLOv8 in accurately detecting leaf diseases, demonstrating its potential in real-time disease identification and classification.

IV. CONCLUSION

In conclusion, the assessment of ResNet34, MobileNetv2, and Yolov8 for corn leaf disease classification reveals subtle differences and trade-offs between the models. Yolov8 is a strong candidate for real-world applications because it continuously exhibits high precision, recall, accuracy, and F1-scores across all disease categories. With its exceptional ability to distinguish between Blight and Common Rust and its exceptional accuracy in recognizing healthy leaves, Yolov8 is a reliable option for precise disease detection. Although ResNet34 and MobileNetv2 show competitive results, Yolov8 performs better overall, particularly in terms of precision and recall. Therefore, the use of Yolov8 in plant disease detection can have a significant impact. By utilizing the Yolov8 model, crop diseases can be detected quickly and accurately. This can help farmers in early detection and targeted treatment of plant diseases, leading to improved crop health and higher yields. Additionally, the Yolov8 model can provide real-time monitoring of crop diseases, allowing farmers to take immediate action and prevent the spread of diseases to other plants in the surrounding areas. Furthermore, the Yolov8 model can also assist in reducing the reliance on manual labor for pest removal, saving time and resources. In summary, the use of Yolov8 in plant disease detection has the potential to revolutionize agricultural practices by providing accurate and efficient detection of crop diseases, leading to improved crop health, higher yields, and reduced reliance on manual labor and excessive pesticide use.

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